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EXAMINER	
PARK, EDWARD	

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Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Office Action Summary	Application No.	Applicant(s)	
	10/806,476	AKAHORI, SADATO	
	Examiner	**Art Unit**	
	EDWARD PARK	2624	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE *3* MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on *12 June 2008*.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) *1-4,17,18,25,26 and 33* is/are pending in the application.

4a) Of the above claim(s) *5-16,19-24,27-32 and 34-36* is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *1,2,4,17,18,25,26 and 33* is/are rejected.

7)☒ Claim(s) *3* is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☒ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on *06 August 2004* is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☒ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☒ All b)☐ Some * c)☐ None of:

1.☒ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☒ Information Disclosure Statement(s) (PTO/SB/08) Paper No(s)/Mail Date *8/6/04*.

4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .

5) ☐ Notice of Informal Patent Application

6) ☐ Other: _____.

DETAILED ACTION

Election/Restrictions

1. Applicant's election without traverse of Species I which consists of claims 1-4, 17-18, 25-26, and 33 in the reply filed on 6/12/08 is acknowledged.

Specification

2. The title of the invention is not descriptive. A new title is required that is clearly indicative of the invention to which the claims are directed.

Claim Objections

3. **Claims 1, 17, 25** are objected to because of the following informalities:

Regarding **claim 1**, on pg. 89, line 26, it appears the phrase, "leaning winner vector", has a typographical error and should be changed to "learning winner vector".

Regarding **claim 17**, on pg. 103, line 22, it appears the phrase, "leaning winner vector", has a typographical error and should be changed to "learning winner vector".

Regarding **claim 25**, on pg. 110, line 24, it appears the phrase, "leaning winner vector", has a typographical error and should be changed to "learning winner vector".

Appropriate correction is required.

Claim Rejections - 35 USC § 101

4. 35 U.S.C. 101 reads as follows:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

The USPTO "Interim Guidelines for Examination of Patent Applications for Patent Subject Matter Eligibility" (Official Gazette notice of 22 November 2005), Annex IV, reads as follows:

> Descriptive material can be characterized as either "functional descriptive material" or "nonfunctional descriptive material." In this context, "functional descriptive material" consists of data structures and computer programs which impart functionality when employed as a computer component. (The definition of "data structure" is "a physical or logical relationship among data elements, designed to support specific data manipulation functions." The New IEEE Standard Dictionary of Electrical and Electronics Terms 308 (5th ed. 1993).) "Nonfunctional descriptive material" includes but is not limited to music, literary works and a compilation or mere arrangement of data.
>
> When functional descriptive material is recorded on some computer-readable medium it becomes structurally and functionally interrelated to the medium and will be statutory in most cases since use of technology permits the function of the descriptive material to be realized. Compare In re Lowry, 32 F.3d 1579, 1583-84, 32 USPQ2d 1031, 1035 (Fed. Cir. 1994) (claim to data structure stored on a computer readable medium that increases computer efficiency held statutory) and Warmerdam, 33 F.3d at 1360-61, 31 USPQ2d at 1759 (claim to computer having a specific data structure stored in memory held statutory product-by-process claim) with Warmerdam, 33 F.3d at 1361, 31 USPQ2d at 1760 (claim to a data structure per se held nonstatutory).
>
> In contrast, a claimed computer-readable medium encoded with a computer program is a computer element which defines structural and functional interrelationships between the computer program and the rest of the computer which permit the computer program's functionality to be realized, and is thus statutory. See Lowry, 32 F.3d at 1583-84, 32 USPQ2d at 1035.

5. **Claims 17-18** are rejected under 35 U.S.C. 101 because the claimed invention is directed to non-statutory subject matter as follows. Claims 17-18 define a data learning program embodying functional descriptive material. However, the claim does not define a computer-readable medium or computer-readable memory and is thus non-statutory for that reason (i.e., "When functional descriptive material is recorded on some computer-readable medium it becomes structurally and functionally interrelated to the medium and will be statutory in most cases since use of technology permits the function of the descriptive material to be realized" – Guidelines Annex IV). The scope of the presently claimed invention encompasses products that are not necessarily computer readable, and thus NOT able to impart any functionality of the

recited program. The examiner suggests amending the claim(s) to embody the program on "computer-readable medium" or equivalent; assuming the specification does NOT define the computer readable medium as a "signal", "carrier wave", or "transmission medium" which are deemed non-statutory (refer to "note" below). Any amendment to the claim should be commensurate with its corresponding disclosure.

Note:

"A transitory, propagating signal … is not a "process, machine, manufacture, or composition of matter." Those four categories define the explicit scope and reach of subject matter patentable under 35 U.S.C. § 101; thus, such a signal cannot be patentable subject matter." (*In re Petrus A.C.M. Nuijten;* Fed Cir, 2006-1371, 9/20/2007).

Should the full scope of the claim as properly read in light of the disclosure encompass non-statutory subject matter such as a "signal", the claim as a whole would be non-statutory. In the case where the specification defines the computer readable medium or memory as statutory tangible products such as a hard drive, ROM, RAM, etc, as well as a non-statutory entity such as a "signal", "carrier wave", or "transmission medium", the examiner suggests amending the claim to ***include*** the disclosed tangible computer readable media, while at the same time ***excluding*** the intangible media such as signals, carrier waves, etc.

Claim Rejections - 35 USC § 102

6. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

A person shall be entitled to a patent unless –

(a) the invention was known or used by others in this country, or patented or described in a printed publication in this or a foreign country, before the invention thereof by the applicant for a patent.

(b) the invention was patented or described in a printed publication in this or a foreign country or in public use or on sale in this country, more than one year prior to the date of application for patent in the United States.

(e) the invention was described in (1) an application for patent, published under section 122(b), by another filed in the United States before the invention by the applicant for patent or (2) a patent granted on an application for patent by another filed in the United States before the invention by the applicant for patent, except that an international application filed under the treaty defined in section 351(a) shall have the effects for purposes of this subsection of an application filed in the United States only if the international application designated the United States and was published under Article 21(2) of such treaty in the English language.

7. **Claims 1, 2, 4, 17, 18, 25, 26, 33** are rejected under 35 U.S.C. 102(b) as being anticipated by Jones et al (US 7,099,510 B2).

Regarding **claim 1**, Jones discloses a data learning apparatus comprising:

first learning means for deriving a temporary self-organizing map in which classes are associated with respective vector points of reference feature vectors by learning first learning data including a plurality of first sample feature vectors for each of which a

corresponding class is known (see fig. 1, col. 5, lines 63-67, col. 6, lines 1-11; object detector 28 includes a classifier 30 (e.g., classification function based on one or more features of an object) that evaluates an image 22 or part of an image 22 to determine if an instance 38 of the object is detected or not); and

second learning means for modifying the temporary self-organizing map and deriving a final self-organizing map by learning second learning data including a plurality of second sample feature vectors for each of which a corresponding class is known (see fig. 1, col. 6, lines 17-27; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the

training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server);

wherein the second learning means includes:

second vector specifying means for reading one of the second sample feature vectors out of the second learning data and specifying a second learning winner vector on the temporary self-organizing map which has the highest similarity to said one of the second sample feature vectors (see col. 9, lines 4-30; classifier 30 (classification function) has more than one feature 54, then the classifier 30 is based on the summation of the threshold functions h; if the sum indicated in equation is greater than this threshold; weight w and global threshold, theta, are determined in a learning phase based on a training data set);

modification means for comparing a class associated with a vector point of the second learning winner vector to a corresponding class of said one of the second sample feature vectors indicated by the second learning data (see col. 9, lines 4-30) and, when the class associated with the vector point of the second learning winner vector is not identical to the corresponding class indicated by the second learning data, modifying the second learning winner vector and a plurality of reference feature vectors distributed in a second learning vicinity of the second learning winner vector on the temporary self-organizing map so as to reduce the similarity thereof to said one of the second sample feature vectors (see col. 12, lines 33-40; AdaBoost approach is used both to select a small set of features 54 for each classifier 30 and the perform the initial training of the classifier 30; learning phase uses the AdaBoost learning procedure to determine the number, N, of features 54 evaluated, the weights, w.sub.j, feature

thresholds, T.sub.j, and the global threshold, .theta., for each classifier 30, thus producing optimal homogeneous classification functions 30); and

means for deriving the final self-organizing map by operating each of the second vector specifying means and the modification means once or repeatedly more than once for each of said plurality of second sample feature vectors (see col. 12, lines 25-32, col. 14, lines 24-32; AdaBoost approach is utilized to perform the initial training of the classifier and learning phase uses the AdaBoost learning procedure for classification functions).

Regarding **claim 2**, Jones discloses modifying the second learning winner vector (see col. 12, lines 40-51) and said plurality of reference feature vectors distributed in the second learning vicinity so as to increase the similarity thereof to said one of the second sample feature vectors, when the class associated with the vector point of the second learning winner vector is identical to the corresponding class of said one of the second sample feature vectors indicated by the second learning data (see col. 12, lines 33-40; AdaBoost approach is used both to select a small set of features 54 for each classifier 30 and the perform the initial training of the classifier 30; learning phase uses the AdaBoost learning procedure to determine the number, N, of features 54 evaluated, the weights, w.sub.j, feature thresholds, T.sub.j, and the global threshold, .theta., for each classifier 30, thus producing optimal homogeneous classification functions 30).

Regarding **claim 4**, Jones discloses plurality of first sample feature vectors and said plurality of second sample feature vectors is a vector having feature quantities indicating features of an image as components thereof (see fig. 1, col. 5, lines 63-67, col. 6, lines 1-11, fig. 1, col. 6, lines 17-27; object detector 28 includes a classifier 30 (e.g., classification function based on one or more features of an object) that evaluates an image 22 or part of an image 22 to determine if

an instance 38 of the object is detected or not; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server), and

each of the corresponding classes indicated by the first learning data (see fig. 1, col. 5, lines 63-67, col. 6, lines 1-11; object detector 28 includes a classifier 30 (e.g., classification function based on one or more features of an object) that evaluates an image 22 or part of an image 22 to determine if an instance 38 of the object is detected or not) and the second learning data is a class indicating a meaning of an image (see fig. 1, col. 6, lines 17-27; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server).

Regarding **claim 17**, Jones discloses a data learning program (see col. 6, lines 28-35; a computer program product, provides software instructions for the object detector 28) for making a computer operate as:

first learning means for deriving a temporary self-organizing map in which classes are associated with respective vector points of reference feature vectors by learning first learning data including a plurality of first sample feature vectors for each of which a

corresponding class is known (see fig. 1, col. 5, lines 63-67, col. 6, lines 1-11; object detector 28 includes a classifier 30 (e.g., classification function based on one or more features of an object) that evaluates an image 22 or part of an image 22 to determine if an instance 38 of the object is detected or not); and

second learning means for modifying the temporary self-organizing map and deriving a final self-organizing map by learning second learning data including a plurality of second sample feature vectors for each of which a corresponding class is known (see fig. 1, col. 6, lines 17-27; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server);

wherein the second learning means includes:

second vector specifying means for reading one of the second sample feature vectors out of the second learning data and specifying a second learning winner vector on the temporary self-organizing map which has the highest similarity to said one of the second sample feature vectors (see col. 9, lines 4-30; classifier 30 (classification function) has more than one feature 54, then the classifier 30 is based on the summation of the threshold functions h; if the sum indicated in

equation is greater than this threshold; weight w and global threshold, theta, are determined in a learning phase based on a training data set);

modification means for comparing a class associated with a vector point of the second learning winner vector to a corresponding class of said one of the second sample

feature vectors indicated by the second learning data (see col. 9, lines 4-30) and, when the class associated with the vector point of the second learning winner vector is not identical to the corresponding class indicated by the second learning data, modifying the second learning winner vector and a plurality of reference feature vectors distributed in a second learning vicinity of the second learning winner vector on the temporary self-organizing map so as to reduce the similarity thereof to said one of the second sample feature vectors (see col. 12, lines 33-40; AdaBoost approach is used both to select a small set of features 54 for each classifier 30 and the perform the initial training of the classifier 30; learning phase uses the AdaBoost learning procedure to determine the number, N, of features 54 evaluated, the weights, w.sub.j, feature thresholds, T.sub.j, and the global threshold, .theta., for each classifier 30, thus producing optimal homogeneous classification functions 30); and

means for deriving the final self-organizing map by operating each of the second vector specifying means and the modification means once or repeatedly more than once for each of said plurality of second sample feature vectors (see col. 12, lines 25-32, col. 14, lines 24-32; AdaBoost approach is utilized to perform the initial training of the classifier and learning phase uses the AdaBoost learning procedure for classification functions).

Regarding **claim 18**, Jones discloses plurality of first sample feature vectors and said plurality of second sample feature vectors is a vector having feature quantities indicating features

of an image as components thereof (see fig. 1, col. 5, lines 63-67, col. 6, lines 1-11, fig. 1, col. 6, lines 17-27; object detector 28 includes a classifier 30 (e.g., classification function based on one or more features of an object) that evaluates an image 22 or part of an image 22 to determine if an instance 38 of the object is detected or not; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server), and

each of the corresponding classes indicated by the first learning data (see fig. 1, col. 5, lines 63-67, col. 6, lines 1-11; object detector 28 includes a classifier 30 (e.g., classification function based on one or more features of an object) that evaluates an image 22 or part of an image 22 to determine if an instance 38 of the object is detected or not) and the second learning data is a class indicating a meaning of an image (see fig. 1, col. 6, lines 17-27; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server).

Regarding **claim 25**, Jones discloses a computer-readable recording medium carrying a data learning program (see fig. 1, numeral 180, col. 6, lines 28-35; a computer program product,

including a computer readable or usable medium (e.g., one or more CDROM's) provides software instructions for the object detector 28) for making a computer operate as:

first learning means for deriving a temporary self-organizing map in which classes are associated with respective vector points of reference feature vectors by learning first learning data including a plurality of first sample feature vectors for each of which a

corresponding class is known (see fig. 1, col. 5, lines 63-67, col. 6, lines 1-11; object detector 28 includes a classifier 30 (e.g., classification function based on one or more features of an object) that evaluates an image 22 or part of an image 22 to determine if an instance 38 of the object is detected or not); and

second learning means for modifying the temporary self-organizing map and deriving a final self-organizing map by learning second learning data including a plurality of second sample feature vectors for each of which a corresponding class is known (see fig. 1, col. 6, lines 17-27; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server);

wherein the second learning means includes:

second vector specifying means for reading one of the second sample feature vectors out of the second learning data and specifying a second learning winner vector on the temporary self-organizing map which has the highest similarity to said one of the second sample feature vectors

(see col. 9, lines 4-30; classifier 30 (classification function) has more than one feature 54, then the classifier 30 is based on the summation of the threshold functions h; if the sum indicated in equation is greater than this threshold; weight w and global threshold, theta, are determined in a learning phase based on a training data set);

modification means for comparing a class associated with a vector point of the second learning winner vector to a corresponding class of said one of the second sample feature vectors indicated by the second learning data (see col. 9, lines 4-30) and, when the class associated with the vector point of the second learning winner vector is not identical to the corresponding class indicated by the second learning data, modifying the second learning winner vector and a plurality of reference feature vectors distributed in a second learning vicinity of the second learning winner vector on the temporary self-organizing map so as to reduce the similarity thereof to said one of the second sample feature vectors (see col. 12, lines 33-40; AdaBoost approach is used both to select a small set of features 54 for each classifier 30 and the perform the initial training of the classifier 30; learning phase uses the AdaBoost learning procedure to determine the number, N, of features 54 evaluated, the weights, w.sub.j, feature thresholds, T.sub.j, and the global threshold, .theta., for each classifier 30, thus producing optimal homogeneous classification functions 30); and

means for deriving the final self-organizing map by operating each of the second vector specifying means and the modification means once or repeatedly more than once for each of said plurality of second sample feature vectors (see col. 12, lines 25-32, col. 14, lines 24-32; AdaBoost approach is utilized to perform the initial training of the classifier and learning phase uses the AdaBoost learning procedure for classification functions).

Regarding **claim 26**, Jones discloses plurality of first sample feature vectors and said plurality of second sample feature vectors is a vector having feature quantities indicating features of an image as components thereof (see fig. 1, col. 5, lines 63-67, col. 6, lines 1-11, fig. 1, col. 6, lines 17-27; object detector 28 includes a classifier 30 (e.g., classification function based on one or more features of an object) that evaluates an image 22 or part of an image 22 to determine if an instance 38 of the object is detected or not; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server), and

each of the corresponding classes indicated by the first learning data (see fig. 1, col. 5, lines 63-67, col. 6, lines 1-11; object detector 28 includes a classifier 30 (e.g., classification function based on one or more features of an object) that evaluates an image 22 or part of an image 22 to determine if an instance 38 of the object is detected or not) and the second learning data is a class indicating a meaning of an image (see fig. 1, col. 6, lines 17-27; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server).

Regarding **claim 33**, Jones discloses an apparatus for determining meanings of a target image or an image region by use of a self-organizing map obtained after learning, said self-organizing map having meanings of images associated with respective vector points thereon, comprising:

extraction means for extracting one or a plurality of feature vectors from the target image or the image region (see fig. 2, numeral 32, col. 6, lines 57-67; image scanner 32 then scans the integral image 44 to divide the integral image 44 into subwindows 42);

winner vector specifying means for specifying a winner vector on the self-organizing map which has the highest similarity to the feature vector for each of said one or plurality of feature vectors (see col. 9, lines 4-30; classifier 30 (classification function) has more than one feature 54, then the classifier 30 is based on the summation of the threshold functions h; if the sum indicated in equation is greater than this threshold; weight w and global threshold, theta, are determined in a learning phase based on a training data set);

meaning determining means for determining the meaning of the target image or the image region based on meanings associated with respective vector points of the winner vectors (see col. 5, lines 63-67, col. 6, lines 1-11);

input means for receiving designation of a target image or an image region of which a correct meaning cannot have been determined by the meaning determining means, and input of the correct meaning of said target image or said image region (see col. 12, lines 62-67, col. 13, lines 1-29); and

modification means for modifying the self-organizing map by additionally learning the target image or the image region which is designated through the input means (see fig. 1, col. 6, lines

17-27; training server 37 is used in the learning phase of to train the classifiers 30 (classification functions) based on a training data set that includes digital images with predetermined or known instance of the object as well as negative examples images showing what the object is not; the training server 37 function to train the classifiers 30 that is, the object detector 28 then uses the classifiers 30 to detect object representations 38 in images 22 without requiring further input from the training server), wherein, for each of one or a plurality of feature vectors extracted from the designated target image or image region, the modification means modifies a winner vector having the highest similarity to the feature vector and a plurality of reference feature vectors distributed in a vicinity of the winner vector on the self-organizing map so as to reduce the similarity thereof to said feature vector (see col. 12, lines 33-40; AdaBoost approach is used both to select a small set of features 54 for each classifier 30 and the perform the initial training of the classifier 30; learning phase uses the AdaBoost learning procedure to determine the number, N, of features 54 evaluated, the weights, w.sub.j, feature thresholds, T.sub.j, and the global threshold, .theta., for each classifier 30, thus producing optimal homogeneous classification functions 30).

Allowable Subject Matter

8. **Claim 3** is objected to as being dependent upon a rejected base claim, but would be allowable if rewritten in independent form including all of the limitations of the base claim and any intervening claims.

Regarding **claim 3**, none of the references of record alone or in combination suggest or fairly teach a first vector specifying means for reading one of first sample feature vectors out of

the first learning data and specifying a first learning winner vector on the initial self-organizing map which has the highest similarity to said one of the first sample feature vectors;
update means for modifying the first learning winner vector and a plurality of reference feature vectors distributed in a first learning vicinity of the first learning winner vector on the initial self-organizing map so as to increase the similarity thereof to said one of the first sample feature vectors, and for increasing the specified frequency values in points corresponding to respective vector points of the first learning winner vector and said plurality of reference feature vectors distributed in the first learning vicinity on a frequency map corresponding to a corresponding class of said one of the first sample feature vectors indicated by the first learning data; means for deriving the temporary self-organizing map by operating each of the first vector specifying means and the update means once or repeatedly more than once for each of said plurality of first sample feature vectors; and means for defining a class which is most likely to appear at each vector point on the temporary self-organizing map as the class associated with said vector point by referring to said plurality of frequency maps.

Conclusion

9. Any inquiry concerning this communication or earlier communications from the examiner should be directed to EDWARD PARK whose telephone number is (571)270-1576. The examiner can normally be reached on M-F 10:30 - 20:00, (EST).

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Vikkram Bali can be reached on (571) 272-7415. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

Information regarding the status of an application may be obtained from the Patent Application Information Retrieval (PAIR) system. Status information for published applications may be obtained from either Private PAIR or Public PAIR. Status information for unpublished applications is available through Private PAIR only. For more information about the PAIR system, see http://pair-direct.uspto.gov. Should you have questions on access to the Private PAIR system, contact the Electronic Business Center (EBC) at 866-217-9197 (toll-free). If you would like assistance from a USPTO Customer Service Representative or access to the automated information system, call 800-786-9199 (IN USA OR CANADA) or 571-272-1000.

Edward Park
Examiner
Art Unit 2624

/Edward Park/
Examiner, Art Unit 2624

/Vikkram Bali/
Supervisory Patent Examiner, Art Unit 2624